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Integrating Machine Learning Techniques and the Unified Theory of Acceptance and Use of Technology to Evaluate Drivers for the Acceptance of Blockchain-Based Loyalty Programmes

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Abstract
Blockchain technology is emerging as an innovative solution to overcome the traditional limitations of customer loyalty programmes by offering transparency, decentralization, and interoperability. This study investigates the factors that drive the acceptance of blockchain-based loyalty programmes (BBLPs) among U.S. digital natives. The analysis is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), extended with trust, and incorporates advanced machine learning techniques. The main objectives are: (1) to generate an exploratory, data-driven understanding of the factors that explain and predict the acceptance of BBLPs using Decision Tree Regression (DTR) and its ensemble extensions—Random Forest (RF) and Extreme Gradient Boosting (XGBoost); and (2) to identify the relative importance of explanatory variables in predicting the behavioural intention to use BBLPs. The results show that while DTR effectively captures how variables interact to generate acceptance, and RF provides a slightly greater predictive capability to XGBoost and both predict better than DTR. According to the Shapley Additive Explanations metric, performance expectancy emerges as the most influential factor in the intention to use BBLPs, followed by trust, facilitating conditions and effort expectancy. Social influence and prior experience using loyalty programmes have a moderate impact, while gender plays a marginal role. This study reinforces the relevance of the UTAUT model in the analysis of emerging technologies and highlights the value of integrating machine learning and interpretability to understand blockchain acceptance patterns in a marketing context.

Keywords Blockchain · Blockchain-based loyalty programmes · UTAUT · Explainable machine learning · Decision tree regression · Random forest · Extreme gradient boosting · Shapley additive explanations

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1 Introduction

Blockchain, introduced in 2008 (Nakamoto, 2008), stands among the foremost transformative technologies of the 21 st century (Tripathi et al., 2023). Unlike centralised technologies, blockchain offers a set of distinctive properties, such as decentralisation, immutability of records, transparency, traceability, cryptographic security, and resistance to tampering (Al-Dulaimi et al., 2023). Blockchain is being implemented across various sectors, including Industry 4.0, supply chain management, digital identity, property registration, electronic voting (Tripathi et al., 2023), and commodity markets such as carbon trading (Dong et al., 2024).

The usefulness of blockchain in marketing is increasingly recognised. It encompasses a broad range of applications, including digital advertising, consumer data protection, product authenticity verification, supply chain traceability, and digital identity management (Shaikh et al., 2023; Wasiq et al., 2023). One of the most promising areas is its application to loyalty programmes (LPs) (Rejeb et al., 2020). Traditionally, LPs have faced challenges related to fragmentation, low user engagement, and a lack of transparency in the accumulation and redemption of rewards (Steinhoff & Palmatier, 2016). Blockchain technology offers a powerful solution to these limitations. This has led to the emergence of blockchain-based loyalty programmes (BBLPs), a new generation of loyalty schemes that harness decentralisation, traceability, and interoperability to provide more transparent, secure, and flexible experiences for both companies and consumers (Treiblmaier & Petrozhitskaya, 2023).

This study examines the factors driving the adoption of BBLPs among so-called digital natives, i.e., individuals born from 1990 onwards who have grown up in digitally mediated environments. The sample includes both younger millennials and members of Generation Z. These generations exhibit distinct patterns in their relationship with technology compared to previous cohorts such as Generation X or the Baby Boomers, showing greater affinity, familiarity, and openness toward digital innovations (Akçayır et al., 2016). Whereas older generations such as Gen X tend to express greater skepticism, ethical concerns, and resistance to technological change, digital natives tend to adopt new tools more rapidly in both educational and professional settings (Chan & Lee, 2023).

The theoretical foundation of this study is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which integrates elements from previous models such as the Technology Acceptance Model (TAM) (Davis, 1989) and its extension, TAM2 (Venkatesh & Davis, 2000) that is extended with the addition of trust. Both TAM and UTAUT have been widely applied to model the adoption of emerging technologies, including blockchain applications in areas such as cryptocurrencies (Bommer et al., 2023), supply chains (Taherdoost, 2022), and more recently, blockchain-based loyalty programmes (BBLPs) (Arias-Oliva et al., 2024).

The proposed theoretical framework is presented in Fig. 1, where the behavioural intention to use BBLPs (BIBBLP) is explained by seven variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), trust (TR), gender (GEN), and prior experience with LPs (EXP). Based on this model, the study pursues two main research objectives (RO):

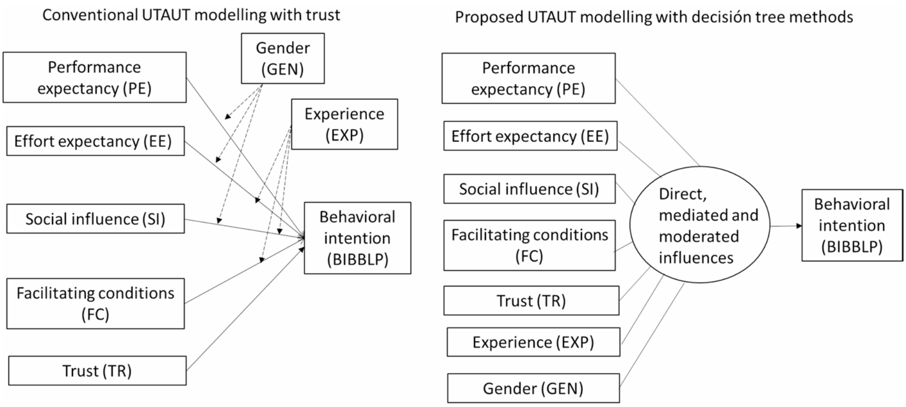


Fig. 1 Conventional UTAUT Framework vs. the adaptation used in this paper

> RO1: To generate an exploratory, data-driven understanding of the factors that explain and predict the acceptance of BBLPs using machine learning (ML) techniques.
> RO2: To determine the relative importance of the explanatory variables and the relevance of their interaction in predicting the behavioural intention to use BBLPs.

In contrast to conventional empirical approaches based on linear models such as Partial Least Squares-Structural Equation Modelling (PLS-SEM), this study employs a ML approach. ML has become increasingly valuable in behavioural marketing due to their capacity to generate accurate and generalisable behavioural predictions (Hagen et al., 2020). Specifically, Decision Tree Regression (DTR) models are applied for their interpretability, along with their ensemble extensions: Random Forest (RF) (Breiman, 2001) and Extreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016). Both RF and XGBoost enhance predictive accuracy by aggregating multiple trees—RF through bagging and XGBoost through sequential boosting optimisation.

Unlike traditional regression models, which rely on linearity assumptions and predefined interactions, tree-based models can automatically capture nonlinear relationships and emergent interactions directly from the data (Loh, 2011). Their hybrid use further strengthens predictive capacity, explaining their growing adoption in economic and business analytics. Recent applications include commodity price forecasting (Tissaoui et al., 2023), assessment of inequality-oriented policies (Motahar & Mamipour, 2025), and bankruptcy prediction (Ben-Jabeur et al., 2023; Navarro-Galera et al., 2025).

ML is particularly well-suited to analysing complex behavioural phenomena such as technology adoption (Chung et al., 2023; Pérez-Portabella et al., 2025) and consumer decision-making (Imani et al., 2025; Imani & Arabnia, 2023)—the focus of this paper. For example, TAM3 (Venkatesh & Bala, 2008) posits that the effects of SI and FC are mediated by perceived usefulness and perceived ease of use, respectively, while UTAUT introduces moderating effects of GEN and EXP. In contrast, tree-based models allow the identification of complex, nonlinear dependencies among explanatory variables and their influence on BBLP acceptance without imposing rigid theoretical structures (Cuc et al., 2025).

Finally, to interpret the model outputs, the paper used the Shapley Additive Explanations (SHAP) measure (Lundberg & Lee, 2017). SHAP decomposes the impact of every predictor to the overall model prediction, providing transparency and interpretative depth to the ML-based analysis (Tissaoui et al., 2023). Moreover, it offers the opportunity to examine how variables interact to produce the predicted outcome (Lundberg et al., 2020).

2 Theoretical Background

2.1 General Overview of Proposed UTAUT Model

Studying the factors that drive the acceptance of a given technology requires framing the problem within a theoretical model that allows for the subsequent application of analytical tools capable of testing both the explanatory and predictive power of the model against empirical evidence.

The outcome variable in this study is acceptance, measured through behavioural intention. This construct can be defined as an individual's willingness to adopt a specific behaviour (Ajzen, 2002). Behavioural intention is commonly used in UTAUT-based models to assess technology acceptance (Venkatesh et al., 2003, 2012). In this case, it refers specifically to the intention to use blockchain-based loyalty programmes (BIBBLP).

It is important to note that blockchain applications have not yet reached full technological maturity, limiting their widespread accessibility (Grover et al., 2019). Therefore, measuring acceptance through behavioural intention—rather than actual use—enables a more homogeneous comparison among potential users, avoiding biases arising from unequal access to the technology (Arias-Oliva et al., 2024).

Literature reviews on blockchain technology acceptance identify the most frequently used conceptual frameworks as TAM, its extension TAM2, and the UTAUT and UTAUT2 models (Almekhlafi & Al-Shaibany, 2021; Taherdoost, 2022). This study is grounded in the original UTAUT model (Venkatesh et al., 2003), and thus considers four core variables to explain acceptance: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), hereafter referred to as the UTAUT-baseline variables.

Both UTAUT and its extensions recognise as moderators, gender, age, and experience (Venkatesh et al., 2003, 2012). Since this study focuses on a generationally homogeneous population, only gender (GEN) and task-specific experience related to loyalty programmes use (EXP) are included as moderators of the outcome variable. Following the terminology used in the original UTAUT model, we refer to these as UTAUT-moderating variables.

2.2 Machine Learning Approaches in Technology Acceptance Research

Although structural equation modelling remains the predominant approach in assessing the acceptance of blockchain applications (Souto-Romero et al., 2025), ML has become increasingly applied in technology adoption studies. The growing interest in predictive analytics in information systems and consumer behaviour research has further accelerated the integration of ML methods into technology acceptance frameworks.

Recent contributions illustrate this methodological shift. As summarised in Table 1, a diverse set of ML techniques—ranging from decision tree–based models, such as RF and XGBoost, to artificial neural networks (ANNs) and support vector machines (SVMs)—has been applied to predict behavioural intention or usage in domains including robo-advisors (Chung et al., 2023), mobile learning (Alhumaid et al., 2021; Almaiah et al., 2021), shared autonomous vehicle adoption (Guo et al., 2025), AI-supported accounting practices (Cuc et al., 2025), fintech behaviours (Abbas et al., 2025), and generative AI usage (Pérez-Portabella et al., 2025). These studies consistently show that ML techniques often outperform traditional statistical models in predictive accuracy and offer complementary insights by identifying thresholds, nonlinearities, and interaction effects.

Regarding explainability, several variable importance approaches have been employed across this literature. Early studies relied primarily on impurity-based importance measures (e.g., Gini or variance reduction) and sensitivity analysis, especially in ANN-based models. More recent research has incorporated advanced explainable ML techniques such as SHAP, which allow for a more granular decomposition of predictors' contributions to model output and provide both local and global interpretability (Kolomoyets & Dickinger, 2023; Razaghzadeh Bidgoli et al., 2024).

Taken together, literature shown in Table 1 suggests that decision tree–based models such as DTR, RF and XGBoost are particularly well suited for modelling technology acceptance, as they naturally capture nonlinearities and complex behavioural dependencies. At the same time, SHAP has emerged as a robust approach for assessing variable importance in ML-based behavioural prediction. In line with these methodological developments, we formulate hypotheses linked to the direction of the relationships of the explanatory factors outlined in Sect. 2.1 within a UTAUT-based framework. While these hypotheses can be empirically evaluated using DTR, RF and XGBoost enhance the predictive capability of DTR, and SHAP allows quantifying the strength of the contribution of each explanatory factor to BIBBLP.

2.3 Hypothesis about the Link of UTAUT Baseline Factors with Behavioural Intention to Use BBLPs

Performance expectancy (PE) is the degree to which an individual believes that using a technology will help improve their performance in a given task (Venkatesh et al., 2003). It is often found to be the most important latent variable in technology adoption studies. In the context of blockchain, its differential utility over centralised systems include enabling LPs with innovative services that incorporate features of the sharing economy, offering gains in questions such as usability, point consolidation, reward value, benefit expiration, and transferability (Treiblmaier & Petrozhitskaya, 2023). Furthermore, blockchain facilitates the development of noncentralised point alliances, overcoming data-sharing drawbacks among platforms and increasing the value of reward credits via a blockchain-based exchange mechanism (Santos et al., 2023).

Table 1 Some studies using machine learning methods in technology acceptance

Study	Topic/Problem addressed	Machine Learning technique used	Variable importance evaluation (method)
Abbas et al. (2025)	Real-world FinTech adoption based on behavioral data.	Logistic Regression, SVM, RF, XGBoost	Gini Importance + SHAP
Alhumaid et al. (2021)	Continued Mobile Learning use integrating TAM, ECM, and TPB.	PLS-SEM + ANN	Sensitivity Analysis
Almaiah et al. (2021)	Mobile Learning acceptance with an extended TAM.	SEM + ANN	Sensitivity Analysis
Alwabel and Zeng (2021)	Technology acceptance across multiple technologies.	Linear Regression, KNN, DTR, MLP, SVR	Sensitivity Analysis
Bennet et al. (2024)	Startup success prediction combining TAM with real performance indicators.	RF, Logistic Regression	Gini Importance + Sensitivity Analysis
Chung et al. (2023)	Robo-advisor acceptance using predictive modelling.	DTR, RF, Gradient Boosting, ANN	Variable Importance (Gradient Boosting)
Cuc et al. (2025)	AI adoption in accounting based on Big Five traits and AI knowledge.	DTR	Impurity Reduction
Guo et al. (2025)	Psychological factors influencing adoption of Shared Autonomous Vehicles (SAVs).	RF	Gini/Impurity Importance
Imani et al. (2025)	Telecom churn under extreme imbalance scenarios.	RF, XGBoost	No variable importance evaluated
Kolomoyets and Dickinger (2023)	Hotel value-in-use analysis via text mining.	STM, AFINN Sentiment, XGBoost	SHAP
Potrawa and Tetereva (2022)	Hedonic rental pricing with structured and unstructured data.	CNNs (feature extraction), RF	Variable Importance (RF), PDP, LIME
Pérez-Portabella et al. (2025)	Adoption of Generative AI in Spain integrating TPB with ML.	V, RF, XGBoost	SHAP
Razaghzadeh Bidgoli et al. (2024)	Prediction of early-stage startup success to support investment decision-making.	RF, Gradient Boosting, MLP, Logistic Regression, SVM; plus K-means, hierarchical clustering, and DBSCAN.	SHAP values and Permutation Feature Importance.

ANN Artificial Neural Network; *AFINN* AFINN Sentiment Lexicon; *CNN* Convolutional Neural Network; *DTR* Decision Tree Regression; *GB/GBM* Gradient Boosting/Gradient Boosting Machine; *KNN* k-Nearest Neighbors; *LIME* Local Interpretable Model-agnostic Explanations; *ML* Machine Learning; *MLP* Multilayer Perceptron; *OLS* Ordinary Least Squares; *PLS-SEM* Partial Least Squares Structural Equation Modelling; *PDP* Partial Dependence Plot; *RF* RF; *SEM* Structural Equation Modelling; *SHAP* Shapley Additive Explanations; *SVM* Support Vector Machine; *STM* Structural Topic Modelling; *XGBoost* Extreme Gradient Boosting

PE has also consistently been the most influential factor in various blockchain applications assessed using TAM and UTAUT models. This has been demonstrated in sectors such as cryptocurrencies (Albayati et al., 2020; Almuraqab, 2020; Jegerson et al., 2023), supply chain management (Sharma et al., 2023), finance and banking (Chen, 2023; Gan & Lau, 2024; Gil-Cordero et al., 2024), education (Chawla et al., 2024), organisational security-intensive processes (Lian et al., 2020), tourism and travel (Li et al., 2021; Nuryyev et al., 2020), and, notably, blockchain-based loyalty programmes (Arias-Oliva et al., 2024; Souto-Romero et al., 2025).

Hypothesis 1 (H1) *PE is positively related to behavioural intention to use BBLPs.*

Effort expectancy (EE) refers to the perceived ease of use of the evaluated technology (Venkatesh et al., 2003). Alongside PE, EE is a critical factor in explaining blockchain adoption (Grover et al., 2019). Ensuring user-friendliness is essential, particularly for users unfamiliar with blockchain, highlighting the relevance of user-centred development to address usability difficulties in blockchain applications (Jang et al., 2020).

Usability and the quality of web interfaces strongly influence blockchain system acceptance (Gil-Cordero et al., 2024), further confirming the need for intuitive design (Shrestha et al., 2019).

EE has been consistently identified as a significant factor for blockchain acceptance across domains such as cryptocurrency investment (Albayati et al., 2020; Almuraqab, 2020; Fakhrullah et al., 2025), supply chain management (Alazab et al., 2021; Bandinelli et al., 2023; Sharma et al., 2023), banking and finance (Chen, 2023; Gan & Lau, 2024), education (Chawla et al., 2024; Gao & Li, 2021), internal organisational processes (Afifa et al., 2023). It is also a key factor in explaining BBLP acceptance (Souto-Romero et al., 2025).

Hypothesis 2 (H2) *EE is positively related to behavioural intention to use BBLPs.*

Social influence (SI) refers to an individual's perception of how people important to them view their use of a particular technology (Venkatesh et al., 2003). SI is particularly relevant in early stages of adoption, especially when the technology in question—such as blockchain—requires a higher level of technical knowledge compared to more traditional alternatives (Jegerson et al., 2023).

However, the impact of SI may be limited by the general lack of public understanding of mechanisms and potential benefits of blockchain (Treiblmaier & Petrozhitskaya, 2023). In this context, institutional and corporate endorsement becomes crucial, as active engagement by companies can play a key role in promoting BBLP adoption (Chen, 2023). Furthermore, digital media, can significantly enhance the visibility, acceptance, and normalisation of BBLPs (Rejeb et al., 2020).

Numerous studies support the role of SI in blockchain adoption across cryptocurrencies (Albayati et al., 2020; Jegerson et al., 2023), supply chains (Alazab et al., 2021; Bandinelli et al., 2023; Sharma et al., 2023), finance (Chen, 2023), and accounting (Afifa et al., 2023).

Hypothesis 3 (H3) *SI is positively related to behavioural intention to use BBLPs.*

Facilitating conditions (FC) are defined as the extent to which an individual perceives the existence of organisational and technical resources to support the use of a technology (Venkatesh et al., 2003). In the BBLP context, this refers to the user's perception of having the means and support to effectively access and use all of its functionalities (Norbu et al., 2024).

When users perceive adequate support, their experience with the technology is likely to be smoother, promoting greater adoption and engagement (Alazab et al., 2021; Sharma et al., 2023). This is particularly relevant in environments where technical infrastructure or expertise may be limiting factors.

The literature confirms FC as a key determinant in blockchain use intention, both in cryptocurrency investment (Arias-Oliva et al., 2019) and supply chain applications (Alazab et al., 2021; Sharma et al., 2023).

Hypothesis 4 (H4) *FC are positively related to behavioural intention to use BBLPs.*

2.4 Hypothesis about the Link of Trust with Behavioural Intention to Use BBLPs

Trust (TR) in emerging technologies such as blockchain can be understood from two complementary perspectives: cognitive and relational (Glikson & Woolley, 2020). The former refers to the belief that the technology effectively fulfills the purposes for which it was designed. In this regard, the inherent properties of blockchain strengthen cognitive trust by ensuring the reliability and protection of transactions (Bandinelli et al., 2023; Tripathi et al., 2023; Norbu et al., 2024).

Relational trust, on the other hand, is linked to the perception of institutional support and the presence of a recognised authority. Since blockchain eliminates intermediaries and operates without a central controlling entity (Nakamoto, 2008), trust is no longer placed in traditional organizations but in the technological system itself and the actors who sustain it. Thus, rather than a loss of trust, there is a reconfiguration of the object of trust, which shifts from centralised institutions to the technological infrastructure, developers, and algorithmic mechanisms that ensure its operation (Taherdoost, 2022).

Various studies confirm that TR is a key determinant in the adoption of blockchain-based solutions, in financial and educational domains as well as in LPs (Bandinelli et al., 2023; Norbu et al., 2024). In the case of BBLPs, this trust reflects the user's belief in the integrity, security, and reliability of the blockchain system used to manage rewards, as well as in its ability to enhance service quality and customer experience.

Hypothesis 5 (H5) *TR positively relates with behavioural intention to use BBLPs.*

2.5 Hypothesis about the Influence of UTAUT-moderating Variables on Behavioural Intention to Use BBLPs

In the UTAUT and UTAUT2 models, gender (GEN) and experience (EXP) act as moderators of the relationship between core predictors and technology acceptance (Venkatesh et al., 2003, 2012). According to UTAUT, GEN moderates the effect of different predictors: men are more influenced by PE, while women are more affected by EE and SI. EXP, on the other hand, may reduce the influence of EE and SI but strengthen the effect of FC (Venkatesh et al., 2003).

In the context of BBLPs, a study conducted in southern U.S. states using fuzzy set Qualitative Comparative Analysis showed that both GEN and EXP interact with UTAUT2 variables, generating distinct paths that lead to either approval or dissapproval BBLPs (Arias-Oliva et al., 2024). Therefore, while it is reasonable to assume that GEN and EXP influence behavioural intention through interaction with core

UTAUT variables, we do not formulate directional hypotheses regarding the nature of these effects. Accordingly, we propose the following hypotheses:

Hypothesis 6 (H6) *GEN interacts with the UTAUT-baseline factors to produce behavioural intention to use BBLPs.*

Hypothesis 7 (H7) *EXP interacts with the UTAUT-baseline factors to produce behavioural intention to use BBLPs.*

3 Materials and Data Analysis

3.1 Sampling

The paper is based on a survey conducted in the spring of 2024 among individuals aged 18 to 34 residing in the United States. The data collection was supported by a leading global consumer research platform with a strong presence in the U.S. market, which allowed us to leverage its expertise and extensive participant database. The platform also assisted in defining the survey distribution strategy and ensuring appropriate cultural adaptation of the questionnaire.

A stratified sampling strategy was employed, establishing minimum quotas of 40% for both men and women, as well as 40% for the 18–24 and 25–34 age groups. Additionally, a minimum threshold of 15% of participants was set for each of the four commonly recognised U.S. regions (Northeast, Midwest, South, and West). The initial dataset comprised 946 responses; however, following the implementation of quality control procedures to filter out inattentive or unusually rapid submissions, a final sample of 615 valid responses was retained.

The United States stands out as a global leader in the development and experimentation of BBLPs. Leading firms such as Starbucks, National Basketball Association, and Walmart have launched or piloted initiatives that leverage blockchain technology to enhance customer loyalty systems. In parallel, a dynamic ecosystem of startups, which include firms such as Loyal, Qiibee, and Bakkt, is actively working on the creation of interoperable solutions that address the limitations of traditional loyalty platforms (Shaikh et al., 2023). Given this landscape, the United States was chosen as the study context due to its dual leadership in loyalty marketing and blockchain innovation. LPs are deeply ingrained in American consumer behavior, with over 90% of consumers participating in at least one program. Furthermore, both the high level of digital maturity in the United States and its large population of digital-native consumers make it an especially suitable environment for examining behavioral intentions toward adopting BBLPs (Wasiq et al., 2023).

3.2 Sample

Table 2 shows the resulting demographic profile. The majority of participants were male (57.4%), followed by females (40.7%), and a small proportion of non-binary or other gender identities (2%). In terms of age, 43.7% of respondents were between

Table 2 Sample profile (N=615)

Variable	Profile
Sex	Male, 353 (57.40%); Female 250 (40.65%); Other 12 (1.95%)
Age	Between 18 and 24 years 269 (43.74%); between 25 and 34 years 346 (56.26%)
Region	Northeast Region 135 (21.95%); Midwest Region 119 (19.35%); West Region 160 (26.02%); South Region 200 (32.52%); Nonanswered 1 (0.16%)
Academic degree	Less than a high school diploma or equivalent 43 (6.99%); High school diploma or equivalent 201 (32.68%); Some college or associate's degree 160 (26.02%); Bachelor's degree 159 (25.85%); Professional degree 21 (3.41%); Post-graduate degree (Masters, PhD) 31 (5.04%).
Annual household income	Less than $25,000 135 (21.95%); from $25,000 to $49,999 163 (26.50%); from $50,000 to $74,999 128 (20.81%); from $75,000 to $99,999 90 (14.63%); $100,000 or more 86 (13.98%); Nonanswered 13 (2.11%)
Ethnicity	White or Caucasian (not Hispanic or Latino) 232 (37.72%); Latinx, Hispanic, Latino, or Spanish origin 124 (20.16%); Black or African American 111 (18.05%); Asian/Pacific Islander 56 (9.11%); Another race or ethnicity/Nonanswered 92 (14.96%).

18 and 24 years old, and 56.3% fell within the 25–34 age group. Geographically, the sample included participants from the Southern states (32.5%), the Western states (26%), the northeastern states (22%), and the Midwestern states (19.4%).

Regarding educational attainment, most participants had completed secondary education or higher, with 52% having at least a college-level education (26% had in-complete college or associate degrees, 25.9% had a bachelor's degree, and 8.5% had a professional or postgraduate degree). In terms of annual household income, 48% reported earning less than $50,000, whereas 35% reported incomes above that threshold. Finally, in terms of ethnicity, the largest group was non-Hispanic White or Caucasian individuals (37.7%), followed by Hispanic/Latino origin (20.2%), and African/American individuals (18%), with additional representation from Asian/Pacific Islander participants (9.1%) and other or unspecified ethnic groups (15%).

Regarding widely accepted heuristics (Hastie et al., 2009), regression-based ML methods generally require approximately 10 to 30 observations per predictor to minimise overfitting and enhance generalisability. More conservative guidelines recommend up to 100 observations per explanatory variable (Alwosheel et al., 2018). Considering that GEN will be operationalised through two dummy variables, the model incorporates eight explanatory factors in total. Thus, with a sample size of 615 observations, this results in approximately 77 cases per predictor, which can be regarded as adequate.

Another approach commonly used in ML involves evaluating theoretical effect sizes and statistical power as if conventional statistical methods had been applied (Rajput et al., 2023). We conducted such an analysis using G*Power 3.1 (Faul et al., 2009). As is typical in studies of this nature, we assumed the use of a regression model with six explanatory variables, following the structure of the conventional UTAUT framework depicted in Fig. 2. For the whole model assessment, considering a 5% significance level, a statistical power of 80% was achieved for detecting small effect sizes ($f^2 = 0.025$), corresponding to a required coefficient of determination of 2.43%. For individual predictors, at the same significance level, a statistical power of 80% was reached for an effect size of 0.0125.

3.3 Measurement of Variables

To better motivate respondents, the questionnaire began with a brief explanation of blockchain technology and its application to LPs, including examples of well-known brands operating in the U.S. market, such as Starbucks, American Express, Walmart and the National Basketball Association.

The items of the scales used to measure both the dependent variable, behavioural intention, and the independent variables — PE, EE, SI, and FC — are an adaptation of Venkatesh et al. (2003) and Venkatesh et al. (2012). The scale for TR was based in that proposed in Morgan and Hunt (1994). The exact wording of the items for these variables is provided in the appendix.

All responses were collected using a scale ranging from 0 ("strongly disagree") to 10 ("strongly agree"). A broader scale has been recommended by several authors because it offers various advantages over the traditional 4-, 5-, or 7-point formats. On the one hand, it allows for more precise capture of subtle differences in respondents'

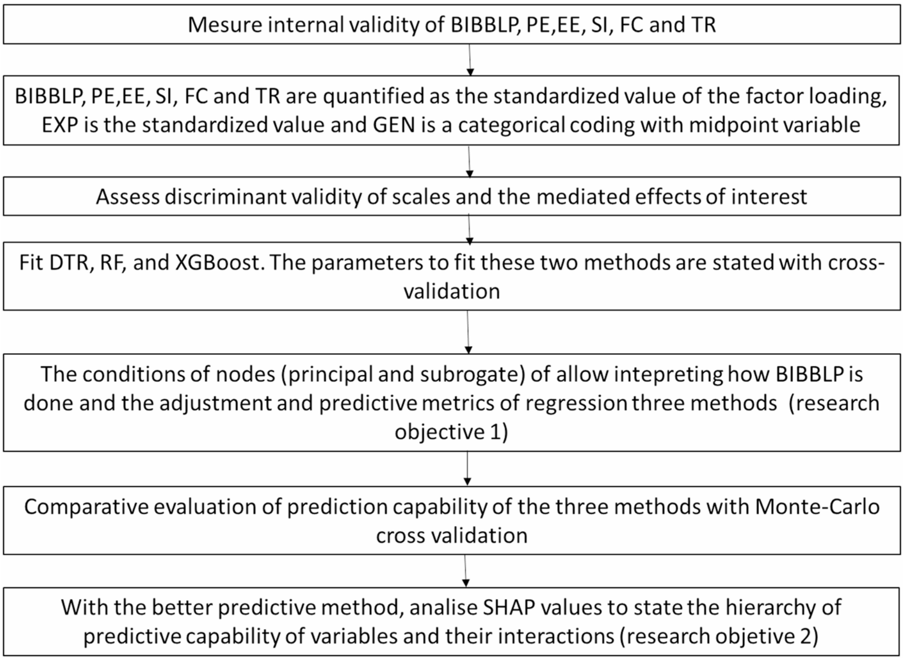


Fig. 2 Methodological workflow for analysing user acceptance of BBLPs with UTAUT and ML methods

perceptions. On the other hand, it provides greater psychometric sensitivity, facilitating closer approximations to interval-level measurement and normal distribution. Furthermore, its 0 to 10 format is intuitive and easy to interpret for most individuals (Leung, 2011). Broader scales, such as those rated from 0 to 10, offer a better balance of reliability, validity, discrimination, and respondent satisfaction than those with fewer than seven points (Preston & Colman, 2000). No previous analysis on reliability of shorter scales was done.

EXP was measured using a single-item indicator capturing the number of LPs in which the respondent was actively enrolled, assessed on an 11-point scale ranging from 0 ("none") to 10 ("10 LPs or more"). This operationalisation aligns with the logic of the original UTAUT framework (Venkatesh et al., 2003, 2012), where experience is conceptualised as an objective and quantifiable indicator—such as duration or amount of exposure to the target technology—rather than as a multidimensional perceptual construct. In the context of loyalty programmes, the number of LPs joined represents a reasonable proxy for users' exposure and familiarity, as participation in multiple programmes typically entails repeated contact with their rules, benefits, and interfaces.

At the same time, we acknowledge that this measure does not capture qualitative aspects such as frequency of use, engagement level, perceived proficiency, or confidence in managing LPs. We also sought to minimise survey length by retaining only essential items and focusing on core constructs, both to facilitate respondent participation and to ensure high-quality data. Importantly, within the UTAUT framework, such experiential elements operate as secondary moderating factors rather than primary determinants of behavioural intention, which further supports the appropriateness of modelling EXP as a single, objectively quantifiable variable.

Lastly, GEN was modelled using two binary variables, with female respondents serving as the baseline category. Specifically, MALE was coded as 1 for respondents identifying as male (0 otherwise), and NBIN was coded as 1 for respondents identifying as non-binary or not exclusively male or female (0 otherwise). This approach avoids imposing an artificial ordinal structure or numerical distance between gender categories.

3.4 Data Analysis with Machine Learning Methods

Figure 2 displays the workflow of the analysis conducted in this paper. Thus, since this paper uses latent variables measured with multiple items, we began by analysing the main descriptive statistics of the items, as well as the internal consistency and convergent validity of the scales. Subsequently, to construct the variable scores, we applied the standardised loading of the first principal component for BIBBLP, PE, EE, SI, and FC, while for EXP, we used the standardised value of the single item composing it. GEN was modelled as two binary variables, MALE and NBIN, as previously described. Based on these values, we assessed the discriminant validity of the scales and examined the direction of the relationships between BIBBLP and the explanatory variables through correlation analysis. The correlations between the explanatory constructs and BIBBLP provide a preliminary test of the empirical validity of the hypotheses proposed in Sect. 2.

Subsequently, although in the UTAUT model the effects of the constructs on behavioral intention are typically modelled as direct impacts, other frameworks such as TAM and its extensions (TAM2 and TAM3) conceptualize the influences of SI and EE on BIBBLP as being partially mediated by PE, while the effect of FC on both BIBBLP and PE is mediated by EE (Venkatesh & Bala, 2008). Accordingly, following Imai et al. (2010), a mediation analysis was conducted to test the potential indirect effects: (1) EE on BIBBLP through PE, (2) SI on BIBBLP through PE, (3) FC on BIBBLP through EE, and (4) FC on PE through EE. Evidence of significant mediation would further suggest the presence of nonlinear relationships among the variables, which can also be captured by the ensemble learning methods employed.

To address RO1, a regression model was estimated using DTR and its generalisations, RF and XGBoost. Model performance was assessed using the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). While RF and XGBoost were expected to yield higher R^2 values, DTR provides a clear visual representation of the threshold values that direct observations toward different nodes. In this sense, the DTR model can be viewed as the most interpretable representation of the patterns captured by RF and XGBoost.

In interpreting the tree splits, if a node condition specifies that variable X must be less than Xa to reach a branch with lower levels of acceptance, this is interpreted as BIBBLP increasing with X. Conversely, if the condition is $X > Xa$, it suggests BIBBLP decreases with X. For this analysis, in addition to the primary splits, we also considered surrogate splits, which help infer the direction of the relationship between explanatory variables and the dependent variable, even when those variables are not selected as main splitters but could serve as valid substitutes. Thus, the evaluation of both primary and surrogate splits in the DTR model allows for empirical testing of the hypotheses set out in Sect. 2.

In the context of regression, decision trees implemented using the CART (Classification and Regression Trees) algorithm aim to recursively partition the predictor space by minimising within-node variance. Once the full tree is built, a cost-complexity pruning procedure is applied to identify the optimal subtree via 10-fold cross-validation, using a complexity parameter that penalises excessive model complexity (Breiman et al., 1984). This process strikes a balance between model fit and parsimony, helping to avoid the overfitting commonly associated with unpruned trees.

To optimise the predictive performance of the RF and XGBoost models, a systematic hyperparameter tuning process was carried out using repeated cross-validation (Imani & Arabnia, 2023). Specifically, we employed a repeated 10-fold cross-validation with three repetitions to ensure result stability and robustness (Alhazeem et al., 2024). For each model, a predefined grid of relevant hyperparameters was explored, and their final values were those that minimsed RMSE.

In the case of the RF model, the hyperparameter tuning process focused on three key parameters: the number of trees (*ntree*), the number of predictors considered at each split (*mtry*), and the minimum node size (*nodesize*). Specifically, the search grid was defined as follows: $mtry = \{1,2,3,4,5,6\}$, $min.node.size = \{1,3,5,10,20\}$, and $num.trees = \{200, 400, 600, 800, 1000\}$. The subsampling rate was held constant during the grid search to ensure comparability across model configurations.

For the XGBoost model, the fine-tuning process focused on four key hyperparameters: the number of boosting rounds (*nrounds*), the learning rate (*eta*), the maximum tree depth (*max_depth*), and the regularization parameter (*gamma*). Other parameters were kept fixed at theoretically and empirically reasonable values following prior studies (e.g., Chen & Guestrin, 2016). Specifically, the minimum child weight (*min_child_weight*) was set to 1, while both the subsampling ratio (*subsample*) and the column sampling ratio (*colsample_bytree*) were fixed at 0.8 to ensure model robustness and prevent overfitting. The grid search explored the following ranges: *nrounds* = {100, 200, 400, 600, 800, 1000}, *eta* = {0.01, 0.05, 0.1, 0.2, 0.3}, *gamma* = {0, 0.1}, and *max_depth* = {2, 3, 4, 5, 6, 7}.

Third, we compared the predictive performance of the three tree-based models using Monte Carlo cross-validation. Evaluating predictive power is useful for both theoretical validation and also to choose models suitable for decision-making in policy and management (Liengaard et al., 2021). Model performance was assessed using Stone-Geisser's Q^2, in addition to RMSE and mean absolute error (MAE). To test for statistically significant differences between methods, ANOVA was applied to RMSE and MAE values, followed by pairwise comparisons using paired t-tests with p-values adjusted via Tukey's method. A total of 500 simulations were conducted, randomly splitting the sample into 80% for training and 20% for testing.

To prevent potential data leakage throughout the entire analytical process, all data handling and modelling operations were performed strictly within each resampling iteration. Specifically, the random 80/20 train–test splits were created before any model fitting, parameter tuning, or metric computation. Since the explanatory variables were already standardised and contained no missing values, no global preprocessing (e.g., scaling, imputation, or feature selection) was applied prior to splitting. The same principle was applied during hyperparameter tuning and model evaluation, ensuring that no information from the test data was used during training and thus preserving the full integrity of the cross-validation and validation procedures.

Finally, to address RO2, the explanatory importance of each variable was assessed using the Shapley Additive Explanations (SHAP) metric, applied to the ML model with the highest predictive accuracy. In addition, the statistical significance of the differences in mean absolute SHAP values between pairs of variables was tested using paired t-tests. The effect sizes of these differences were also evaluated using Cohen's *d* ratio. This procedure allows us to determine not only whether the differences in variable importance are statistically significant but also the magnitude of those effects.

Likewise, SHAP interaction effects were examined to analyse how explanatory variables jointly contribute to producing the model outcome. To keep the analysis tractable, interactions were explored only between the explanatory variables and the one considered the keystone for explaining BIBBLP. In this study, we consider that this variable corresponds to the main split in the first node of the DTR model, as it necessarily interacts with the other major split variables when clustering observations into terminal nodes. This approach follows recent methodological advances in explainable ML, which highlight SHAP interaction values as a robust framework for quantifying and visualising pairwise dependencies between predictors in nonlinear models (Lundberg et al., 2020; Molnar, 2020).

All analyses were implemented in R (version 4.4.2). Descriptive statistics, reliability, and validity assessments of the measurement scales were performed using the *psych* and *lavaan* packages. The computation of the latent variable scores through the extraction of the first principal component was carried out with stats and *FactoMineR*. Correlation analyses and discriminant validity checks were conducted with *Hmisc* and *correlation*. Mediation analyses following the causal mediation framework proposed by Imai et al. (2010) were implemented using the mediation package.

ML models were estimated using the *rpart*, *ranger*, and *xgboost* packages, respectively. Hyperparameter tuning was performed through repeated 10-fold cross-validation using the caret package, while performance metrics (R^2, RMSE, and MAE) were computed with *Metrics* and *dplyr*. Monte Carlo cross-validation with 500 iterations was coded manually to ensure reproducibility and model stability.

For SHAP analysis, values were computed using the *iml* library, and their visualization was generated with *ggplot2* and *viridis*. Pairwise significance tests of SHAP value differences were carried out with *rstatix*, and effect sizes were estimated using *effectsize*. All data wrangling and aggregation procedures were performed with *tidyverse* functions to ensure consistency and transparency in the analytical workflow.

4 Results

4.1 Descriptive Statistics and Measurement Model Assessment

Table 3 presents the basic item statistics. For BIBBLP, the evaluations were clearly more positive than negative, as the mean values consistently exceeded 5 and even 6. The items for PE, EE, SI, and FC all surpassed 6 and, in the case of PE, EE, and FC, often approached 7. Additionally, the average EXP corresponded to participation in nearly five LPs.

It is also worth noting that the mean values across all UTAUT constructs are relatively high, which may indicate a degree of positivity bias in respondents' evaluations. Although such pattern is common in attitudinal studies on technology acceptance (Ciriello & Loss, 2023), the restricted variance may reduce the ability of ML models to capture more subtle behavioural distinctions.

The Cramér–von Mises statistic indicates that a Gaussian distribution cannot be assumed for any of the items. Notably, one advantage of the methods employed in this study is that they do not require the assumption of normality, making them well-suited for analysing non-normally distributed data (Bzdok et al., 2018).

The results also show that the scales used exhibit internal consistency, as Cronbach's alpha and composite reliability exceed the 0.7 threshold in all cases. Convergent reliability is also confirmed, since the average variance extracted (AVE) is above 0.5 for all scales. Likewise, all items showed factor loadings greater than 0.708 (Hair et al., 2019).

Table 4 presents the correlations between the constructs and the squared root of the AVE. The results support the assumption of discriminant validity, as in all cases, the squared root of the AVE for each construct is higher than its Pearson correlation with any other factor. Additionally, none of the inter-construct correlations exceed

Table 3 Descriptive statistics of the items and scale validity measures

Item	Mean	SD	CVM	Factor loading	CA	CR	AVE
Behavioural intention (BIBBLP)					0.858	0.934	0.875
BIBBLP1	6.265	3.008	0.892	0.936			
BIBBLP2	6.250	2.903	0.911	0.936			
Performance expectancy (PE)					0.91	0.937	0.788
PE1	6.779	2.697	1.033	0.877			
PE2	6.829	2.639	1.021	0.903			
PE3	6.803	2.724	1.053	0.907			
PE4	6.821	2.692	1.046	0.863			
Effort expectancy (EE)					0.896	0.935	0.828
EE1	6.878	2.537	1.028	0.917			
EE2	6.717	2.573	0.984	0.915			
EE3	6.932	2.665	0.962	0.896			
Social influence (SI)					0.913	0.945	0.852
SI1	6.156	2.782	1.043	0.923			
SI2	6.119	2.719	1.1	0.934			
SI3	6.228	2.703	0.888	0.912			
Facilitating conditions (FC)					0.886	0.922	0.746
FC1	6.429	2.84	0.735	0.798			
FC2	6.707	2.596	0.916	0.896			
FC3	6.829	2.551	1.016	0.898			
FC4	7.011	2.663	0.91	0.861			
Trust (TR)					0.92	0.944	0.807
TR1	6.834	2.633	0.988	0.903			
TR2	6.842	2.627	0.944	0.896			
TR3	6.577	2.605	0.88	0.904			
TR4	6.789	2.692	0.904	0.891			
Experience (EXP)					1	1	1
EXP1	4.821	3.024	1.49	0.913			

(**a**) SD refers to standard deviation; CVM denotes the Cramér–von Mises statistic; CA stands for Cronbach's alpha; CR is the composite reliability; and AVE represents average variance extracted. (**b**) The CVM test rejects the assumption of normality for all items

the 0.85 threshold, further reinforcing the evidence of adequate discriminant validity (Cheung et al., 2024).

The Pearson correlations between the explanatory variables and BIBBLP (except for NBIN) are positive and statistically significant at the 1% level. These results provide preliminary empirical support for hypotheses H1, H2, H3, H4 and H5, which posit a positive effect of PE, EE, SI, FC and TR on the intention to use BBLPs. They are also consistent with hypotheses H6 and H7, which propose that the moderating variables GEN and EXP influence the acceptance of BBLPs.

The mediation analysis, whose results are presented in Table 5, revealed that most of the indirect effects derived from the theoretical structure proposed by TAM and its extensions are significant. In particular, the influence of EE on BIBBLP was fully mediated by PE, indicating that EE affects behavioural intention primarily through PE. The mediation of SI on BIBBLP through PE showed partial mediation, suggest-

Table 4 Inter-construct correlations and squared roots of average variance extracted (AVE)

	BIBBLP	PE	EE	SI	FC	TR	MALE	NBIN	EXP
BIBBLP	0.936								
PE	0.804	0.888							
EE	0.678	0.803	0.910						
SI	0.593	0.657	0.620	0.923					
FC	0.701	0.781	0.796	0.740	0.864				
TR	0.682	0.749	0.740	0.764	0.807	0.898			
MALE	0.126	0.129	0.063	0.174	0.115	0.132	1.000		
NBIN	−0.047	−0.053	−0.055	−0.064	−0.061	−0.063	−0.095	1.000	
EXP	0.379	0.328	0.275	0.303	0.285	0.287	0.091	−0.074	1.000

(**a**) The principal diagonal displays the squared root of the average variance extracted (AVE). Below the diagonal are the Pearson correlations between the variables. (**b**) With the exception of NBIN, all correlations between explanatory variables and BIBBLP are significant at 1% level

Table 5 Results of the mediation tests of the mediated influence of EE, SI, FC on BIBBLP

Mediation relation	ACME	*p*-value	ADE	*p*-value	TE	*p*-value	PM
EE-> PE-> BIBBLP	0.587	<0.001	0.091	0.064	0.678	<0.001	86.54%
SI-> PE-> BIBBLP	0.479	<0.001	0.114	0.002	0.593	<0.001	80.85%
FC-> EE-> BIBBLP	0.262	<0.001	0.440	<0.001	0.701	<0.001	37.30%
FC-> EE-> PE	0.394	<0.001	0.388	<0.001	0.782	<0.001	50.39%

(**a**) ACME stands for average causal mediated effect (**b**) Average direct effect and TE total effect (**c**) PM is the proportion of the mediated effect respect to the overall effect

ing that SI operates both directly and indirectly via usefulness beliefs. Finally, FC exhibited consistent partial mediations, affecting BIBBLP and PE through EE.

Taken together, these results suggest the existence of nonlinear and interaction effects among constructs—dynamics that linear modelling cannot fully capture. This finding reinforces the methodological rationale for complementing traditional regression analysis with ensemble-based ML approaches (e.g., RF and XGBoost), which are specifically designed to identify and model complex, higher-order interactions in behavioural data.

4.2 Results of Research Objective 1

Table 6; Fig. 3 present the results of the DTR model. As in the correlation and mediation analyses, all variables, except those related to GEN, were quantified as standardised factors (mean = 0, standard deviation = 1). The variable that appears most frequently as the principal split is PE, which appears thrice. The variables EE, TR and EXP also appeared once as the principal condition for splitting. The participation of PE, EE and TR is consistent with the expected positive relationship with BIBBLP, as the conditions leading to nodes associated with lower acceptance involve values below their respective thresholds. Likewise, EXP acts as a variable that is positively related to BIBBLP in the node where it acts as the principal split.

The assessment of surrogate splits provides valuable insights for evaluating the hypotheses proposed in Sect. 2. EE emerges as a surrogate split in the three nodes with the largest number of observations, consistently indicating a positive relation-

Table 6 Principal splits and subrogate splits in the decision three regression nodes (Fig. 3)

	Node 1	Node 2	Node 3	Node 4	Node 5	Node 7
Observations	615	306	309	104	202	139
Primary split	PE< −0.022	PE< −0.859	PE<0.812	TR< −0.209	EXP< −0.101	EE<0.471
Subrogate splits	EE< −0.078	EE< −1.109	SI<0.840	SI< −0.054	PE<−0.339	FC< −0.028
	FC<0.079	FC< −1.064	EE<0.710	FC<0.606	EE<−0.231	
	SI<0.055	TR<−0.952	FC<0.735		SI< −0.323	
	TR < −0.010	SI< −0.990	TR<0.838		FC< −0.945	
	EXP<0556		EXP<1.217		TR<−0.0025	

(**a**) The first row shows the condition used to construct the fitted decision tree in the Fig. 3. (**b**) The conditions apply to guide observations toward lower-level nodes associated with a lower level of BEINT (i.e., "to the left"). (**c**) The values of variables are standardised factor loadings (**d**) The considered adjusted agreements of subrogate splits are >0.1

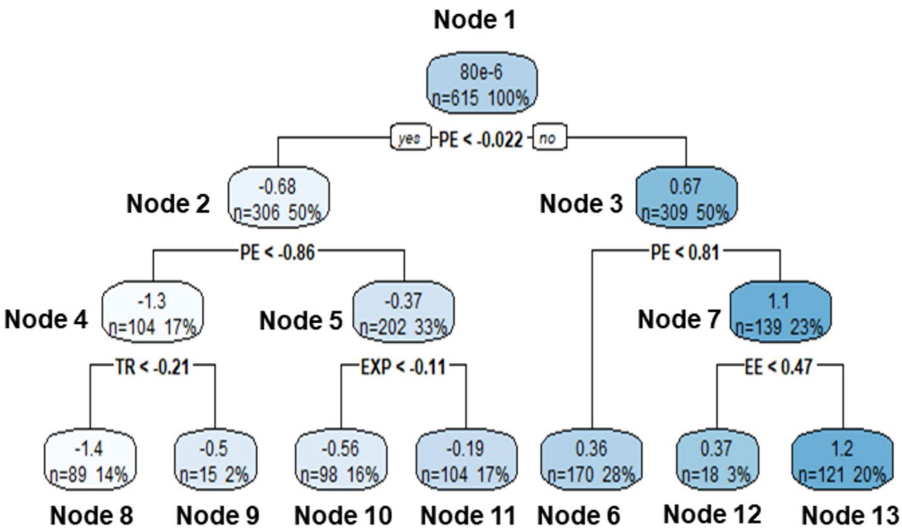


Fig. 3 Explanatory DTR of BIBBLP. *Note*: Within the oval of each node comes the mean value in the node of the standardised BIBBLP measure, the number of observations in the node and the proportion that observations in the node suppose over the overall sample

ship with BIBBLP, as reflected by threshold values such as −0.078 in Node 1. A similar pattern is observed for TR, which appears as a surrogate split in four nodes, also suggesting a positive association with BIBBLP. Although FC and SI do not appear as primary splits, both variables act as surrogate splits—FC across all nodes and SI in almost all, except Node 7. In both cases, their potential as splitting variables aligns with their positive correlations with BIBBLP. It is also noteworthy that PE appears as a surrogate split in Node 5, which contains 202 observations, and also with the expected sign.

Regarding the UTAUT-moderating variables, EXP appears not only as a main split in Node 5, but also as a surrogate split in Nodes 1 and 3. In all instances, the thresholds for EXP were the upper limits of the observations classified as lower levels of acceptance.

Therefore, the interpretation of the DTR results is consistent with H1 (PE), H2 (EE), H3 (SI), and H4 (FC) and H5 (TR). Furthermore, the fact that EXP appears as a main split in one node and as a surrogate split in three, and that GEN (in the form of both MALE and NBIN) has no relevance to build up the tree suggests that only EXP may interplay with the UTAUT-baseline variables and TR to influence BBLP acceptance. Thus, H6 can be rejected but H7 cannot be ruled out.

Subsequently, RF and XGBoost models were also fitted. The RF architecture was selected using repeated 10-fold cross-validation with three repetitions. The best-performing configuration was achieved with *ntree* = 600, *nodesize* = 3, and *mtry* = 3. During the fine-tuning process based on RMSE minimisation, the model achieved an average RMSE of 0.5876 with a standard deviation of 0.0109, indicating high stability across validation folds.

The final XGBoost model was also selected based on the hyperparameter combination that yielded the lowest RMSE during repeated 10-fold cross-validation (three repetitions). The optimal configuration included *nrounds* = 600, *eta* = 0.01, and *max_depth* = 3, *gamma* = 0, while all other parameters were fixed (*colsample_bytree* = 0.8, *min_child_weight* = 1, subsample = 0.8). The fine-tuning process resulted in an average RMSE of 0.6333 with a standard deviation of 0.0301.

Table 7 presents the model fit statistics for DTR, RF, and XGBoost for the full sample. There is a clear superiority in explanatory power for the advanced versions of DTR, while DTR achieves an R^2 of 65.84%, indicating moderate to substantial fit (Hair et al., 2019), RF explains approximately 94.94% of the variance and XGBoost 80.18%. However, this difference should not be interpreted as a dismissal of the DTR model because the methods are better understood as complementary. Ensemble methods, such as RF and XGBoost, enhance the adjustment performance of the DTR by combining numerous decision trees. In contrast, the DTR model produces a single, easily interpretable structure that explicitly illustrates the relationships between independent and dependent variables.

Table 8 summarizes the predictive performances of the different methods evaluated using the three metrics. In all cases, the positive value of the Q^2 statistic indicates that the model proposed in Sect. 2 can accurately anticipate the outcomes, regardless of the estimation technique used. As all Q^2 values exceed 50%, the predictive capacity of the model can be considered high (Hair et al., 2019).

This result supports the practical utility of the proposed UTAUT-based model when implemented using DTR, RF, and XGBoost, from a predictive perspective. Likewise, as we expected, RF and XGBoost outperforms DTR.

The results presented in Table 9 indicate that, among the decision tree–based models, RF provides the highest predictive performance. This conclusion is supported by the ANOVA tests conducted on the error metrics RMSE and MAE, as well as on the predictive fit indicator Q^2. The results allow us to reject the null hypothesis of equal mean performance across all methods. Table 9 presents the post-hoc pairwise com-

Table 7 Model fit results for DTR, RF, and XGBoost using the full sample

Method	R^2	RMSE	MAE
Decision Tree Regression	65.84%	0.5845	0.4615
Random Forest	94.94%	0.2425	0.1798
XGBoost	80.18%	0.4491	0.3344

Table 8 Predictive performance of ML methods with Monte Carlo cross-validation

Method	Q^2	RMSE	MAE
Decision Tree Regression	58.60%	0.645	0.502
Random Forest	66.00%	0.582	0.444
XGBoost	65.30%	0.588	0.447
ANOVA	F = 314 (< 0.001)	F = 349(< 0.001)	F = 561 (< 0.001)

(**a**) F stands for Snedecor's F, and in parentheses comes the p-value of ANOVA test

Table 9 Statistical tests on the differences in mean errors of paired methods

	RMSE			MAE		
	Mean difference	t-ratio	*p*-value	Mean difference	t-ratio	*p*-value
DTR vs. RF	0.063	19.97	< 0.001	0.058	24.89	< 0.001
DTR vs. XGBoost	0.057	18.16	< 0.001	0.055	23.57	< 0.001
RF vs. XGBoost	−0.006	−1.81	0.071	−0.003	−1.32	0.253

parison analysis, which confirms that RF significantly outperforms DTR. However, it should also be noted that the slightly superior performance of RF over XGBoost is not statistically significant.

4.3 Results of Research Objective 2

The SHAP beeswarm plot in Fig. 4 offers two key insights into the explanatory structure of the RF. First, in terms of relative importance, the most influential variables are, in this order, PE, TR and/or FC, as indicated by the broader horizontal spread of their SHAP values. These are followed by EE, SI, and EXP, whereas GEN (split into MALE and NBIN) appears to contribute less to the predictions of the model. This ranking reflects the extent to which each variable drives variance in the predicted BIBBLP.

The color gradient helps to interpret the direction of influence. For PE, the brightest colors (high values) are clustered to the right, indicating that higher PE leads to increased predicted intention to use. A similar pattern is observed for TR, FC and EE, and with less clarity, for EXP and SI where higher values also correspond to positive SHAP contributions, reinforcing their role as facilitators of adoption. These patterns confirm the theoretical expectations of the UTAUT framework displayed in Sect. 2 and provide empirical support through a nonlinear, interpretable ML lens.

Figure 5 displays the mean absolute SHAP values computed from the RF model. The results reveal that PE contributes the most to the model's predictions, as it exhibits the highest average SHAP value. This finding is consistent with its strong correlation with BIBBLP and with the fact that PE constitutes the primary decision node in most of the partitions of the decision tree illustrated in Fig. 2. Of particular note is the role of TR and FC as the second and third most influential variables, respectively—even though FC does not appear as a main splitter in any part of the tree. This importance becomes understandable when considering that FC shows the second-highest Pearson correlation with BIBBLP and acts as a surrogate split in all intermediate

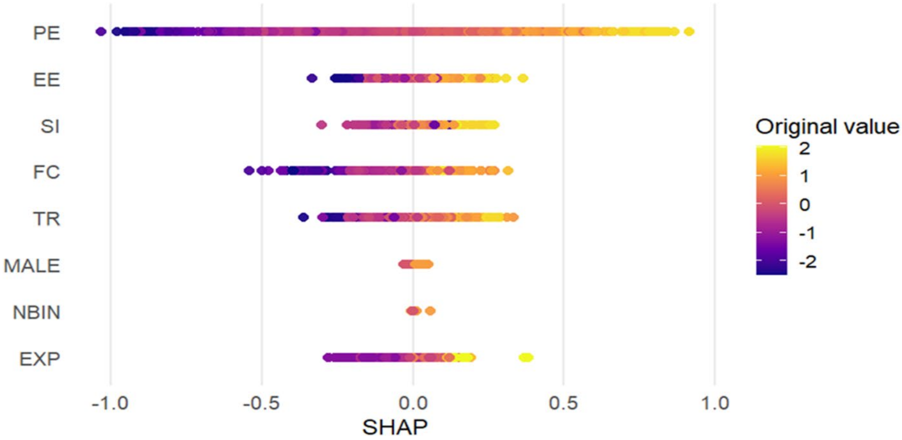
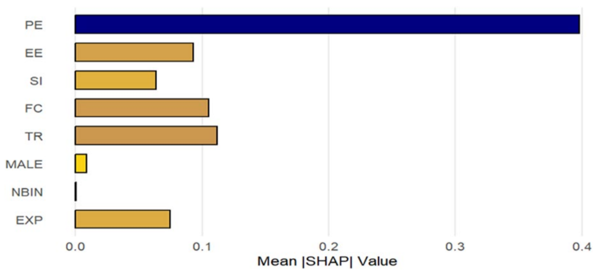


Fig. 4 SHAP beeswarm plot of explanatory factors importance and direction in the RF adjustment. *Note*: Each point represents a single observation, with SHAP values indicating how much each variable contributes to increasing or decreasing the predicted BIBBLP. The colour gradient represents the original (feature) value of each variable—from low (dark purple) to high (yellow)—so that warmer tones (yellow) indicate higher values of the predictor. Positive SHAP values to the right of the zero line denote a stronger positive contribution to BIBBLP, whereas negative values to the left represent inhibitory effects

Fig. 5 Mean of absolute SHAP of all embedded variables in the model



nodes of the DTR model depicted in Fig. 3. Finally, the minimal role of dummy variables linked to GEN in the tree structure, is consistent with its very low SHAP contribution, confirming it as the least influential variable in the model.

Table 10 presents the pairwise mean difference tests for the SHAP values, revealing a clear and consistent ranking pattern. PE emerges as significantly more important than all other variables, with a very large effect size ($d > 1$). All of the remaining differences are also statistically significant, with effect sizes ranging from small (e.g., $d = 0.14$ for FC > EE) to very large (e.g., $d = 1.50$ for TR > NBIN). However, it is worth noting that although the slightly higher mean SHAP value of TR over FC is significant at the 5% level ($p = 0.048$), the corresponding effect size is nearly negligible ($d = 0.08$). Overall, the explanatory variables can be ranked in importance as PE > TR $\gtrsim$ FC > EE > EXP > SI > GEN.

Figure 6 displays the SHAP dependence plots illustrating the interactions between PE and the remaining predictors (EE, SI, FC, TR, EXP, and MALE only for GEN) in

Table 10 Testing the significance of the pairwise differences of the mean absolute SHAP

Var 1	Var2	SHAP1	SHAP2	difference	t-ratio	*p*-value	Cohen's d
PE	EE	0.398	0.093	0.305	35.39	<0.001	1.43
PE	SI	0.398	0.064	0.335	36.53	<0.001	1.47
PE	FC	0.398	0.105	0.293	34.30	<0.001	1.38
PE	TR	0.398	0.112	0.286	34.47	<0.001	1.39
PE	MALE	0.398	0.008	0.390	40.34	<0.001	1.63
PE	NBIN	0.398	0.000	0.398	40.97	<0.001	1.65
PE	EXP	0.398	0.074	0.324	33.06	<0.001	1.33
EE	SI	0.093	0.064	0.029	10.43	<0.001	0.42
EE	FC	0.093	0.105	−0.012	−3.36	<0.001	0.14
EE	TR	0.093	0.112	−0.019	−7.01	<0.001	0.28
EE	MALE	0.093	0.008	0.085	30.58	<0.001	1.23
EE	NBIN	0.093	0.000	0.093	33.30	<0.001	1.34
EE	EXP	0.093	0.074	0.019	5.06	<0.001	0.20
SI	FC	0.064	0.105	−0.042	−10.20	<0.001	0.41
SI	TR	0.064	0.112	−0.049	−16.52	<0.001	0.67
SI	MALE	0.064	0.008	0.055	25.58	<0.001	1.03
SI	NBIN	0.064	0.000	0.063	28.43	<0.001	1.15
SI	EXP	0.064	0.074	−0.011	−3.91	<0.001	0.16
FC	TR	0.105	0.112	−0.007	−1.98	0.048	0.08
FC	MALE	0.105	0.008	0.097	25.92	<0.001	1.05
FC	NBIN	0.105	0.000	0.105	28.22	<0.001	1.14
FC	EXP	0.105	0.074	0.031	6.92	<0.001	0.28
TR	MALE	0.112	0.008	0.104	35.19	<0.001	1.42
TR	NBIN	0.112	0.000	0.112	37.28	<0.001	1.50
TR	EXP	0.112	0.074	0.038	9.80	<0.001	0.39
MALE	NBIN	0.008	0.000	0.008	26.38	<0.001	1.06
MALE	EXP	0.008	0.074	−0.066	−29.12	<0.001	1.17
NBIN	EXP	0.000	0.074	−0.074	−32.14	<0.001	1.30

Var1 and Var2 stands for variables, and SHAP1 and SHAP2 the mean of absolute SHAP of these variables

shaping BIBBLP. We excluded NBIN due to the negligible value of its mean absolute SHAP displayed in Fig. 5. Note that PE is the most influential variable in the model and, as shown in the decision tree in Fig. 3, the primary splitter at the first node, making it the pivotal explanatory construct. Across all panels, the relationship between PE and its SHAP values is clearly positive and approximately monotonic, indicating that higher levels of PE consistently increase the predicted likelihood of adopting BBLPs.

The colour gradients, representing the values of the interacting variables, reveal synergistic effects. In the interactions with EE, SI, FC, and TR, lighter (yellow) points cluster in the upper-right region, showing that higher levels of these variables amplify the positive influence of PE on BBLPs. This suggests that perceived usefulness becomes more influential when users also perceive greater EE, SI, FC and TR. For EXP, the interaction remains positive though more moderate, suggesting that greater EXP slightly reinforces the impact of PE, especially at higher PE levels.

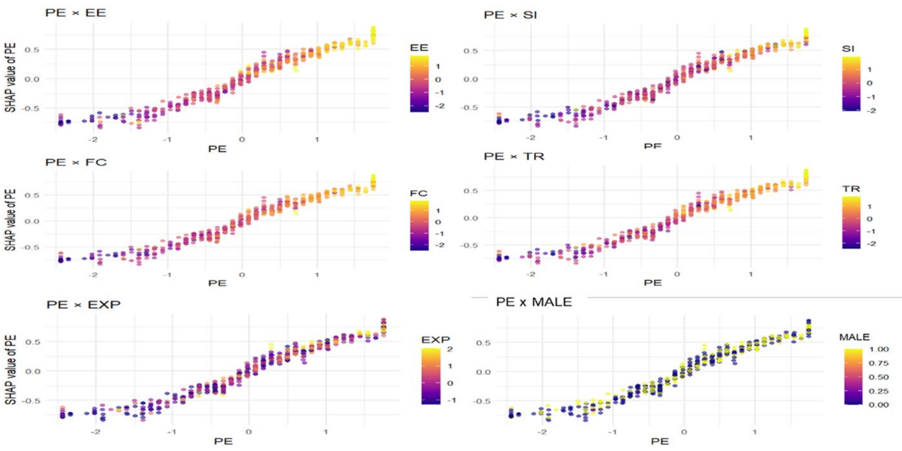


Fig. 6 SHAP Dependence plots of the interaction effects between performance expectancy and the other explanatory variables. *Note*: Each panel shows how the SHAP value of PE varies with its original value and with another explanatory variable (EE, SI, FC, TR, EXP, MALE). The colour gradient (dark purple = low, yellow = high) indicates the interacting variable's value. Higher PE values consistently increase BIBBLP, especially when EE, TR, or FC are also high

Conversely, MALE exhibits a similar upward trend, but colour variation is limited, implying it plays only a minor moderating role in the relationship between PE and BIBBLP.

5 Discussion

5.1 General Reflections

This study pursued two research objectives. The first (RO1) was to propose and empirically examine a UTAUT-based framework, implemented through machine learning (ML) techniques, to explore its ability to explain and predict the behavioural intention to engage with blockchain-based loyalty programmes (BIBBLP). The second (RO2) aimed to determine the relative importance of the explanatory variables in predicting the intention to use such programmes. The results obtained provide answers to both objectives.

Regarding RO1, the three ML models used—Decision Tree Regression (DTR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—demonstrated strong explanatory and predictive capabilities, all clearly exceeding the minimum acceptable thresholds in terms of R^2 and cross-validated Q^2 values. Although the DTR model exhibited a lower R^2 compared to RF and XGBoost, it proved particularly valuable due to its interpretability, which is crucial for understanding the phenomenon of adoption. RF and XGBoost, for their part, achieved outstanding levels of model fit, highlighting the suitability of ensemble methods for analysing technology acceptance.

Concerning RO2, the SHAP analysis revealed that the most influential variable in behavioural intention to use BBLPs (BIBBLP) was performance expectancy (PE), followed by trust (TR), and facilitating conditions (FC). Effort expectancy (EE), prior experience in using loyalty programmes (EXP) and social influence (SI), showed lower levels of importance. The prominence of PE in explaining BIBBLP aligns with both the theoretical foundations of the technology acceptance literature, which identifies PE as a key determinant (Davis, 1989; Venkatesh et al., 2003), and with recent studies on blockchain applications (Taherdoost, 2022), including BBLPs (Souto-Romero et al., 2025). Gender (GEN), in either of its two dummy-variable categories, displayed residual relevance.

Although it is somewhat surprising that FC emerged as more relevant than EE or SI in predicting BIBBLP, the literature has emphasised the importance of FC in contexts such as cryptocurrency use (Arias-Oliva et al., 2019) and supply chain management (Sharma et al., 2023).

EE also played a relatively important role—greater than that of SI, EXP, and GEN—in explaining BIBBLP. This was evident both in the primary and surrogate splits of the DTR model and in the SHAP values derived from the RF estimation. The relevance of EE has been consistently documented in the blockchain adoption literature, across various domains such as cryptocurrency (Albayati et al., 2020; Almuraqab, 2020; Fakhrullah et al., 2025), supply chain management (Bandinelli et al., 2023; Sharma et al., 2023), the financial and banking sector (Gan & Lau, 2024), and specifically in the context of BBLPs (Souto-Romero et al., 2025).

Although it may seem notable that SI is less relevant than PE, EE, FC and TR in explaining behavioural intention, this finding is consistent with previous studies reporting non-significant effects of SI in blockchain adoption research. Such findings have been observed in supply chain management (Alazab et al., 2021; Kamble et al., 2019), cryptocurrency usage (Arias-Oliva et al., 2019), and financial services (Gan & Lau, 2024).

Finally, both EXP contributed modestly to the explanation of BIBBLP, to a lesser extent than three baseline UTAUT variables (PE, EE, FC) and TR. This is consistent with its original conceptualisation as moderating variables of the UTAUT core constructs (Venkatesh et al., 2003). However, EXP shows a stronger contribution than SI. One plausible explanation is that users' direct exposure to LPs—possibly including BBLPs or frequent interactions through related digital channels (apps, e-mails, social media)—may have a more immediate impact on their perceptions of BBLPs than interpersonal influence. In contrast, the type of interpersonal interaction captured by SI (e.g., friends, colleagues, family) is likely limited in this context, as LPs are not a common topic in everyday conversations. Thus, higher EXP may translate into more digitally mediated cues, while traditional interpersonal influence remains marginal. This result should nevertheless be interpreted with caution, as EXP was measured using a single-item indicator that does not capture broader experiential dimensions such as frequency of use, perceived competence, or confidence.

Regarding GEN (that was split in two dummy variables), the results were that this variable is not relevant, suggesting that traditional gender differences in technology adoption have largely diminished. The stratified sampling ensured similar digital competence across subgroups, reducing the likelihood of systematic disparities. Additionally, the motivational drivers behind BIBLLPs —such as transparency, trust, and convenience—are largely gender-neutral, which helps explain the absence of stable gender effects.

To assess potential overfitting, we compared the in-sample explanatory power (R^2) with the out-of-sample predictive accuracy (Q^2) obtained from the Monte Carlo cross-validation procedure. As shown in Tables 6 and 7, all models display the expected reduction in predictive performance when moving from estimation to validation, but the differences remain moderate. Specifically, RF exhibits the largest drop, whereas XGBoost shows the smallest, suggesting a more balanced trade-off between fit and generalizability. These findings are consistent with the stability observed during the hyperparameter fine-tuning process, where both RF and XGBoost achieved low RMSE variability across folds and repetitions, indicating reliable and robust convergence of model parameters. Overall, the models appear adequately calibrated and not severely overfitted, reinforcing the validity of the cross-validation and tuning procedures implemented in this study.

5.2 Implications for Theory

From a theoretical standpoint, the findings reinforce the validity of the UTAUT model as a robust explanatory framework for the acceptance of emerging technologies, even in specific applications such as BBLPs. The confirmation of hypotheses H1 to H5 through the DTR model, along with further support provided by SHAP values in the RF model, suggests that the core constructs of the UTAUT model maintain and TR their predictive power in novel and highly disruptive technological environments.

Furthermore, the results underscore the value of integrating ML techniques into technology acceptance research. These approaches help overcome certain limitations of traditional methods (such as PLS-SEM), as they do not rely on assumptions of linearity or pre-specified interaction structures. The capacity of tree-based models to identify nonlinear relationships, threshold effects, and emergent interactions among variables proves particularly useful in complex behavioural contexts.

The use of the SHAP metric contributes an additional layer of interpretability. This method enables transparent decomposition of individual predictions and assigns a relative weight to each variable, thereby producing a hierarchy of explanatory importance that deepens the understanding of the phenomenon under investigation. In this sense, the findings resonate with the growing body of literature advocating the combination of predictive modelling and interpretability techniques as a promising direction for advancing research on technology-related behaviour.

The evidence regarding the moderating variables (H6 and H7) suggests that whereas EXP may exert differential effects on acceptance, GEN has a very low influence. The DTR model shows that EXP operates as a primary split in at least one node and as a surrogate split in others, whereas GEN has no influence.

The fact that trust TR emerges as a stronger predictor than EE and SI can be interpreted as a direct consequence of the technological and still nascent nature of BBLPs. In environments where technology remains complex, opaque, or lacks established social norms—as is the case with blockchain—trust operates as a cognitive compensatory mechanism that mitigates perceived uncertainty and facilitates user interaction and adoption (Glikson & Woolley, 2020).

FC also emerged as a stronger determinant of behavioral intention than both EE and SI and with similar power than TR. This pattern can be attributed to the contextual characteristics of BBLPs, where users rely heavily on platform infrastructures that abstract away technical complexity. As a result, the EE functions as a baseline expectation, whereas the availability of resources, interoperability, and technical support become decisive enablers of adoption. Furthermore, in technologically mature environments, users' high levels of digital literacy diminish the relative importance of EE, while FC continues to differentiate adoption intention. The limited influence of SI likewise reflects the early diffusion stage of blockchain applications, in which social norms and peer effects remain underdeveloped.

5.3 Managerial Implications

From a practical perspective, the findings of this study offer important implications for loyalty programmes designers, marketing professionals, and developers of blockchain-based solutions. Firstly, the prominence of PE as the primary explanatory factor suggests that BBLPs should focus on delivering tangible and clearly perceived benefits to users. This involves designing programmes that provide concrete functional advantages, such as ease of accumulating and redeeming rewards, interoperability across brands, and transparency in transactions. In this sense, token interoperability mechanisms and cross-brand reward portability can significantly enhance users' perception of utility, while incorporating gamification elements (e.g., progress levels, challenges, or token-based achievements) can further stimulate engagement and perceived value.

Secondly, the significance of FC highlights the importance of ensuring that users have access to the necessary resources, information, and support to use BBLPs effectively. This may translate into the development of intuitive interfaces, educational materials (e.g., tutorials and explanatory videos), specialised customer support, and onboarding strategies aimed at reducing the learning curve associated with blockchain technologies. Additionally, integrated wallet solutions and user-friendly transaction tracking features can further lower entry barriers and enhance perceived control.

Although EE has a lower relative weight than PE and FC, it still has a meaningful impact on acceptance. This reinforces the value of user-centred design and functional simplicity. The more intuitive and accessible the use of a BBLP, the greater the likelihood of its adoption. As such, usability should be treated as a core design principle. Designers might, for instance, prioritise minimalistic interfaces, streamlined token redemption flows, and clear visual feedback to facilitate seamless user interaction.

While SI exerts less explanatory power, its role should not be overlooked—particularly during the early stages of technological diffusion. Communication and marketing strategies should include mechanisms that promote network effects, such as engagement with digital influencers, user testimonials, and social recommendation features. Moreover, visible endorsements from reputable brands may contribute to legitimising the use of BBLPs among consumers. Social leaderboards or community-based reward challenges may also be leveraged to reinforce peer validation and participation.

Finally, although GEN does not emerge as a robust determinant, EXP appears to be a relevant factor. Segmentation strategies could benefit from identifying user profiles with high familiarity with LPs, as these individuals are more likely to adopt blockchain-based variants. Targeted campaigns could therefore be designed to engage these segments as early adopters or advocates for technological change.

6 Conclusions

6.1 Main Findings

This study addressed two research objectives: to develop a theoretical framework based on the UTAUT model integrated with ML techniques to explain and predict the intention to use blockchain-based loyalty programmes (BBLPs) (RO1), and to establish the relative importance hierarchy of the explanatory factors (RO2).

The decision tree-based models—particularly RF and XGBoost—demonstrated strong model fit, clearly surpassing the thresholds commonly accepted in the literature. Although DTR exhibited comparatively lower predictive performance, its interpretative strength renders it a valuable tool for theoretical insight.

The SHAP analysis, applied to the most accurate predictive model, revealed that PE is the leading determinant of usage intention, followed by FC and EE. SI and EXP also contributed, though to a lesser extent. Gender showed residual explanatory power.

6.2 Limitations of the Study

This study presents several limitations that should be acknowledged. Firstly, the sample comprised exclusively digital natives residing in the United States, which restricts the generalisability of the findings to older generations and other sociocultural contexts. Prior research on technology acceptance has shown that older cohorts—such as Generation X and Baby Boomers—exhibit distinct patterns of acceptance when it comes to financial technologies, particularly regarding concerns related to privacy, institutional trust, and risk aversion. These generational groups often engage in different financial decision-making processes, shaped by varying levels of financial literacy and familiarity with digital tools. Documented disparities in digital confidence and financial capability indicate that older individuals frequently report lower levels of confidence in adopting technological innovations for financial purposes (Mussa et al., 2023). Such perceptions may result in greater skepticism and resistance toward modern technologies, especially in contexts involving personal data and privacy risks.

Secondly, this is a cross-sectional assessment that does not allow stating hard causal relationships or the analysis of temporal dynamics among the constructs examined. Moreover, the high mean values observed across several items suggest a potential positivity bias in respondents' evaluations. While such tendencies are typical in self-reported assessments of novel technologies, the restricted variance may have constrained the ability of the ML models to detect more nuanced behavioural patterns.

Thirdly, the study relied on self-reported measures, which may be subject to social desirability bias or inaccuracies in participants' perceptions. Similarly, the dependent variable measured intention to use, rather than actual usage behaviour—a suitable approach for studying early-stage adoption, but one that limits the generalisability of findings to real-world behaviour.

Moreover, while modelling EXP using a single-item indicator, as in the original UTAUT formulation (Venkatesh et al., 2003), offers simplicity and ease of implementation, the inherent limitations of single-item measures must be acknowledged. Although EXP exhibits a moderate level of importance in the SHAP analysis, comparable to that of SI, this result should be interpreted with caution. The construct is captured solely through the number of LPs in which a respondent participates, and this unidimensional operationalisation does not reflect qualitative aspects of experience such as frequency of use, engagement, perceived proficiency, or confidence. As a consequence, the relative importance of EXP in the model reflects the respondent's degree of exposure rather than a fully developed experiential construct.

The study did not incorporate socio-technical factors that may be particularly salient in blockchain-based environments. Aspects such as the psychological impact of decentralisation, user familiarity with tokenised systems, perceived risk, or privacy concerns were beyond the scope of the current UTAUT-based framework. Nevertheless, these factors could meaningfully moderate or reshape the influence of traditional acceptance variables. Future research should consider integrating such dimensions into extended theoretical models to more accurately capture the unique features of Web3 infrastructures and decentralised technologies.

We acknowledge that the implementation of ML models inherently involves numerous discretionary decisions that may introduce researcher bias. These include the selection of algorithms, the definition of the hyperparameter search space, the choice of optimisation metrics, and the cross-validation strategy. Ultimately, it is impossible to ensure that the chosen algorithm or the resulting hyperparameters represent the absolute optimum; the most rigorous approach is to make the entire tuning and validation procedure explicit and transparent (Lipton & Steinhardt, 2019). Future work could include calibration checks or external validation to further assess model generalizability.

6.3 Future Lines of Research

Future research could enhance the external validity of the model by replicating the study in more diverse populations both generationally and culturally. It may allow to assess whether the observed acceptance patterns hold across different cultural and generational contexts.

Given the early stage of blockchain adoption in most consumer-facing industries, including loyalty programmes, its widespread implementation is likely to unfold gradually. This slow and ongoing diffusion process highlights the importance of conducting longitudinal studies that can monitor changes in user acceptance over time. To strengthen both causal inference and ecological validity, future research should go beyond cross-sectional designs and incorporate behavioral metrics, such as actual usage logs or transaction data from operational BBLP platforms. By combining longitudinal approaches with real-life behavioral tracking, researchers will be better equipped to evaluate the long-term validity of explanatory models like UTAUT and to capture the evolving dynamics of technology adoption as blockchain infrastructures mature.

From a methodological standpoint, it would be valuable to complement the predictive approach with configurational techniques or structural equation modelling to explore the mediating relationships and moderating effects in greater depth. Likewise, although the use of an 11-point Likert-type scale enhances response precision and variance capture, cross-format validation was not conducted. Future studies could experimentally compare 5- and 11-point versions of the same constructs to assess potential response style differences and confirm measurement invariance across scale lengths (Preston & Colman, 2000).

This study relies primarily on behavioral intention rather than actual usage behavior, which is appropriate given the nascent stage of blockchain adoption in loyalty programmes. However, to enhance ecological validity, future research should prioritize the analysis of real usage patterns. As blockchain technology becomes more widely implemented—particularly within loyalty program ecosystems—it will become increasingly feasible to move beyond intention-based models and incorporate actual behavioral data. This shift would enable a more accurate assessment of user engagement and strengthen the empirical grounding of technology acceptance models in real-world contexts.

Finally, future studies are encouraged to explore practical interventions aimed at optimising the design, communication, and onboarding processes of BBLPs and assessing their impact through experimental or quasi-experimental designs.

Appendix

Table 11 Items Employed in this Paper

Behavioural intention (BIBBLP)
BIBBLP1: If a firm I'm engaged provides a LP powered with blockchain, I predict that I'm going to join it.
BIBBLP2: If a firm I'm engaged provides a LP powered with blockchain, I'm going to try to use it.
Performance expectancy (PE)
PE1: The BBLP provides utility.
PE2: This technology will increase the degree to which I can manage my interactions
PE3: With a BBLP will be more efficient for me to check my status and see my transactions in the loyalty program
PE4: The BBLP allows more opportunities than traditional programmes to benefit from loyalty schemes.
Effort expectancy (EE)
EE1: Learning to utilise benefits and digital token units in a BBLP requires no effort.
EE2: Owning and exchanging rewards and tokens in a BBLP will be clear and understandable for me
EE3: This blockchain application is easy to use.
Social influence (SI)
SI1: Relevant persons to me feel that I have to utilise BBLPs.
SI2: Persons influencing me will believe that I have to use the BBLP of my preferred brands
SI3: Persons with valuable opinions feel that I have use the BBLPs of brands.
Facilitating conditions (FC)
FC1: I possess the skills and understanding needed to operate blockchain-based systems.
FC2: Blockchain-based loyalty programmes (BBLPs) align well with the digital tools and technologies I regularly use.
FC3: A user-friendly interface makes BBLPs appear more effective and appealing.
FC4: Access to instructional resources and user support enhances the perceived usefulness of BBLPs.
Trust (TR)
TR1: I am confident that the BBLP system will do the right actions
TR2: I believe that the system has been built up taking into account consumer needs.
TR3: I trust that the system has been thoroughly tested and is error-free
TR4: I trust the security of the BBLP

Experience (EXP): Please think about your Experience in Loyalty Programmes, e.g. grocery stores, frequent flyer programmes, restaurant rewards programmes. Approximately, how many do you belong to? (from 0 (none), 1 (one), 2 (two),…,9 (nine) and 10 (ten or more)

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Data Availability The data used in this paper is available under reasonable request to any author.

Declarations

Informed Consent Permission has been obtained from all participants of the study.

Institutional Review Board Statement (1) All participants were given detailed written in-for mation about the study and procedure; (2) no data directly or indirectly related to the health of the subjects were collected, and thus, the Declaration of Helsinki was not generally mentioned when the subjects were informed; (3) anonymity of the collected data was ensured at all times; (4) the ethical approval of this research was registered by the corresponding author's institution (CEIPSA-2024-PRD-0030).

Conflict of interest The authors declare no conflict of interests.

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